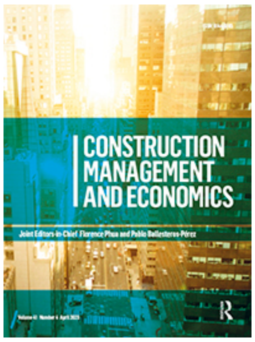

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Impact of industrial agglomeration on total factor productivity in the construction industry: evidence from China

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ABSTRACT

Industrial agglomeration (IA), a common industrial phenomenon, has been verified to have a significant impact on total factor productivity (TFP) in many industries. However, the impact of IA on TFP is seldom investigated in the construction industry, despite the existence of the industrial agglomeration phenomenon in the construction industry. As such, this study aims to probe into the impact of IA on TFP in the construction industry, so as to provide new insights into the industry development and improvement of TFP in the construction industry. Based on the competing results of the agglomeration effect and congestion effect caused by IA, this study proposed three hypotheses on the impact mechanism of IA on TFP in the construction industry. Then, the non-linear regression model and linear regression model were developed to test the hypotheses based on the provincial panel data from 2002 to 2017 in China. The empirical results reveal that IA has a positive linear impact on TFP in the construction industry, and the impact of IA on TFP in the Chinese construction industry during the observed period is in the embryonic stage. Besides, both the firm scale and economic development level have positive impacts on TFP, whereas the specialization structure has a negative impact. Hence, the government can encourage industrial agglomeration in the construction industry to enhance TFP, in order to leverage the knowledge spillovers, labor pool, and other benefits from IA.

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KEYWORDS
Industrial agglomeration; total factor productivity; the construction industry; linear regression model; non-linear regression model

Introduction

The construction industry is always regarded as a pillar of rapid economic growth in China (Zhan and Pan 2020), as it accounted for 7.16% of the National Gross Domestic Product (GDP) (around 1141.65 billion dollars), ranking 5th among all the 19 industries in 2020 (NBSC 2021). However, the productivity of the construction industry is poor in China (F. Yuan *et al.* 2020a), which can be attributed to the labor-intensive and resource-intensive development pattern of the construction industry (J. Zhang *et al.* 2021a). Nowadays, the construction industry is facing a challenge to reduce the negative impact on the labor and environment while maintaining economic growth under the constraint of resources (J. Zhang *et al.* 2021a). Therefore, the improvement of total factor productivity (TFP), a representative concept of high-quality growth for economics (Chen *et al.* 2017, Ye *et al.* 2019; Y. Wang *et al.* 2020), is urgent for the government to facilitate the future development in the construction industry (Zhan and Pan 2020).

The impact factors of TFP should be identified concerning about enhancing the productivity of the construction industry in China (Zhan and Pan 2020). Previous studies have identified different impact factors at different levels, ranging from country, industry, firm to project levels, which mainly include the country's economic development, the industry's market structure, technology and labor development, the firm's strategy, and the construction project management level (Zhan and Pan 2020, Azman *et al.* 2022). As for the country's economic level, such indexes as GDP and consumer price index have become well-recognized influencing factors (Chen *et al.* 2017, Zhan and Pan 2020). In the industry level, the market structures, such as scale structure, ownership structure, specialization-division structure, etc. also have an impact on TFP (B. Liu *et al.* 2015, Chen *et al.* 2017). Besides, the power equipment rate and expenditure on research and development representing the level

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of technology innovation (D. Tan *et al*. 2015, Chen *et al*. 2017) and the quantity of labor (Ye 2019, Zhan and Pan 2020) and the skill level of labor (Zhan and Pan 2020) representing the industry labor development level, are all been found having impacts on productivity. From the perspective of firm's strategies, the product diversification and internationalization of domestic firms have been verified as the influence factors (Azman *et al*. 2021, Azman *et al*. 2022). Regarding the construction project management-related factors, subcontracting management (Zhan and Pan 2020), cost control and quality control (Arditi and Mochtar 2000), etc. have been found to influence TFP.

However, the impact of industrial agglomeration (IA), a common industrial phenomenon, has been seldom discussed in the construction industry, despite various factors have been identified. IA means that the firms in an industry or different industries are geographically clustered, which has been verified to have a significant impact on TFP or productivity in the manufacturing industry (Batisse 2002, Widodo *et al*. 2014), textile industry (Lin *et al*. 2011) and tourism (Kim *et al*. 2021), etc. Besides, these studies also identify the agglomeration effect and congestion effect caused by IA, which impose positive effect or negative effect on productivity. Thus, the net impact on productivity depends on the competition between these two contrary effects in different stages of the agglomeration life cycle (Potter and Watts 2011), probably displaying a negative linear (Batisse 2002) or positive linear (Widodo *et al*. 2014, Kim *et al*. 2021) or non-linear invert U-shaped relationship (Lin *et al*. 2011) between IA and productivity. Although the impact of IA on TFP in the construction industry is seldom investigated, the concentration of contractors found in previous studies revealed the existence of IA phenomena in the construction industry (McCloughan 2004, Zhao *et al*. 2017). Besides, the formation of industrial agglomeration is an important part of industry development which is concerned with the policies and strategies proposed by the government (Zheng and Lin 2018). Therefore, an exploration of the impact of IA on TFP in the construction industry is appealed to provide guides for the government and practitioners to effectively draw a plan for the development of the construction industry, so as to improve TFP in a more targeted manner.

As such, this study aims to verify the impact of IA on TFP in the construction industry and investigate the related impact mechanism. First, competing hypotheses about the relationship between IA and TFP have been proposed. Then, the location quotient (LQ) and Färe-Primont DEA approach were adopted to measure IA and TFP respectively. After that, the provincial panel data of the construction industry in China from 2002 to 2017 were collected and both the non-linear model and linear regression model were established to test the hypotheses. Finally, several suggestions were proposed to improve TFP in the construction industry based on the empirical results in China.

The remainder of this paper is structured as follows. Literature review and hypotheses development are conducted in the next section. Section "Methods and data" presents the selected methods and data. Section "Results and discussions" reports the empirical findings and the corresponding discussions. Conclusions and policy implications are summarized in the final section.

Literature review and hypotheses development

Industrial agglomeration: concept and measurement

Industrial agglomeration (IA) has generally been defined in two ways. One defines this phenomenon as that the firms in the same industry are geographically clustered, leading to Marshallian externalities (localization economies); while the other one defines the IA as the geographical agglomeration of firms from different industries, which results in Jacobs externalities (urbanization economies) (Jacobs 1969, Marshall 1890). Focusing on a single industry (i.e. construction industry), the current study defines industrial agglomeration in the construction industry as that construction firms are geographically clustered in a certain region based on the first general definition (McCloughan 2004, Zhao *et al*. 2017).

Several indicators have been applied to measure the degree of IA, such as Concentration Ratio (CR), Herfindahl-Hirschman index (HHI), Ellison–Glaeser index (EG), and Location Quotient (LQ). The k-firm CR denotes the total market shares of the top k firms in a certain industry (McCloughan 2004). The HHI quantifies the IA level based on the quadratic sum of the market shares of all firms in a certain region (Hirshman 1964). EG combines both industrial and firm-level data to measure the IA more accurately based on the division of the estimated spatial HHI for a given industry to the expected value of HHI, which can eliminate the random effect of specific firms' locations (Ellison and Glaeser 1997, Rivera *et al*. 2014). However, the above three indicators all require available firm-level survey data, while it is difficult and time-consuming to conduct large-scale research across the whole country in China.

In contrast, the location quotient (LQ) is advantageous here as it can measure the IA degree at a larger geographical level without requiring detailed firm-level data. The LQ is an analytical statistic that measures a region's industrial agglomeration relative to a larger geographic unit. The LQ is measured by comparing an industry's share of some economic statistic (e.g. earnings, GDP, employment, etc.) in a specific region with its share of the same statistic in a country (Zhao *et al*. 2017, H. Yuan *et al*. 2020b, Kim *et al*. 2021). Recently, LQ has been adopted to measure the degree of IA in the tourism industry (Kim *et al*. 2021), manufacturing industry (H. Yuan *et al*. 2020b), construction industry (Zhao *et al*. 2017), etc., denoting its practicality and applicability in measuring the level of IA. Therefore, the current study adopted LQ to measure the degree of IA in the construction industry.

Total factor productivity: concept and measurement

Total factor productivity (TFP) is applied to express output as a function of all major inputs. Compared with partial productivity (e.g. labor productivity), TFP has been regarded as an ideal concept for an in-depth productivity analysis (X. Wang *et al*. 2013, Vogl and Abdel-Wahab 2015, Chancellor and Lu 2016, X. Hu and Liu 2017, Zhan and Pan 2020) because it can take other resources (e.g. materials and capital) into the calculation process (Zhan and Pan 2020).

The measurement methods for TFP can be divided into the parametric method and non-parametric method which are represented by Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) respectively (X. Wang *et al*. 2013, X. Hu and Liu 2017, Y. Wang *et al*. 2021). The application of SFA requires setting the specific form of production function in advance, which is difficult to meet the objective situation (X. Hu and Liu 2017). Thus, the results of SFA may be sensitive to the choice of function form and less reliable if sample sizes are small (O'Donnell 2014). But SFA can accommodate errors of approximation and other sources of statistical noise (O'Donnell 2014). DEA is to identify the relative efficiency of each point (i.e. decision-making unit) according to the distance between the point and the frontier that envelopes all the data points (Azman *et al*. 2022, Chancellor and Lu 2016). Although DEA shows weakness in terms of distinguishment inefficiency from noise, the application of DEA does not require any explicit assumptions or the functional form of unknown production frontier compared with SFA (O'Donnell 2014). Therefore, DEA was chosen as the basic measurement method in this study.

For measurement based on the DEA technique, there are two processes to calculate TFP, i.e. Malmquist-based DEA and Färe-Primont DEA (Chancellor and Lu 2016, Azman *et al*. 2019). Although Malmquist-based DEA has been widely applied to estimate the changes in productivity in the construction industry (Xue *et al*. 2008, X. Wang *et al*. 2013), Färe-Primont DEA has several advantages over Malmquist-based DEA (Azman *et al*. 2019). First, Färe-Primont DEA can be decomposed into input-oriented or output-oriented measures, providing detailed insights on productivity analysis (Chancellor and Lu 2016). Second, the establishment of Färe-Primont DEA fits all economical axioms and tests based on index number theory, thus it can be applied to multi-temporal and multi-lateral comparisons (Widodo *et al*. 2014, Chancellor and Lu 2016). Moreover, Färe-Primont DEA has been widely adopted to measure productivity at the industrial level (Chancellor and Lu 2016), which denotes the practicality and applicability to the current study. As such, Färe-Primont DEA was adopted to measure the TFP in the construction industry in this paper.

The effect of industrial agglomeration on total factor productivity in the construction industry

Previous studies have revealed that industrial agglomeration imposes both the agglomeration effect and congestion effect on productivity (Broersma and Van Dijk 2008, Ushifusa and Tomohara 2013, C. Hu *et al*. 2015, J. Liu *et al*. 2017). The former brings about localization externalities which can improve productivity, but the latter may offset the benefits (C. Hu *et al*. 2015). Therefore, the impact of IA on TFP in the construction industry depends on the competing results of the agglomeration effect and congestion effect.

Agglomeration effect of industrial agglomeration in the construction industry

According to Marshall (1890), the economics of scale which results from localization economies provides an economic rationale for the benefits of agglomeration, such as knowledge spillovers, labor market pooling, and input-output linkages, thus leading to the improvement of productivity.

First, knowledge spillovers occur through formal and informal interactions among firms and individuals (e.g. face-to-face meetings, open-day events, shared training, etc.) within the industrial district (Marshall 1890, Connell *et al*. 2014, C. Hu *et al*. 2015). The construction industry can be regarded as a knowledge-based industry because employees need to solve various problems in different construction projects based on experience rather than easily "copy and paste" practice (Pathirage *et al*. 2007, Bakar *et al*. 2016). Therefore, the knowledge spillovers contribute to the improvement of TFP of the construction industry by the quick response of employees to the environment and reducing the cost of solving problems (Z. Wang and N. Wang 2012, Zhan and Pan 2020).

Second, IA can also cluster labor when firms situate in a certain area, forming a labor pool (Marshall 1890). As a labor-intensive industry, the construction industry significantly depends on the quantity and the skill level of the workforce to enhance productivity (El-Gohary and Aziz 2014, Zhan and Pan 2020). Employers can lower the risks of job vacancies and reduce the cost of searching for skilled labor due to a large number of workers in the market (Combes and Duranton 2006, C. Hu *et al*. 2015). Besides, the employees can also lower the relocation cost when they want to leave the original firms that are incompatible with their prospects (Combes and Duranton 2006). The labor pool benefits the improvement of TFP in the construction industry as it can promote frequent job matchings between employees and employers (C. Hu *et al*. 2015).

Third, input-output linkages refer to the ease of sharing inputs and outputs due to the proximity of suppliers, producers, and consumers within a cluster, thus saving transport costs (Marshall 1890, Kim *et al*. 2021). The transportation costs of material conquer a large proportion of the project cost, reaching 39–58% of total logistics costs and 4–10% of the product selling price in the construction industry (Ying *et al*. 2018). The formation of IA can attract upstream and downstream industries to cluster in the same region, which makes it easy for construction firms to find trading partners and save on trade costs (Huo *et al*. 2020).

Congestion effect of industrial agglomeration in the construction industry

Although the agglomeration effect has been verified in extensive studies, IA can also cause congestion effect due to excessive agglomeration, hindering the improvement of productivity (Broersma and Van Dijk 2008, Ushifusa and Tomohara 2013, C. Hu *et al*. 2015, J. Liu *et al*. 2017). The congestion effect can be reflected in two aspects: excessive competition and infrastructure burden (Rizov 2012).

Excessive competition for both projects and production resources will arise as the scale of IA continues to expand (X. Liu and Zhang 2021). First, the excessive competition will lead to an overate of effective demand for the construction market due to the imbalance of supply and demand side, resulting in the underrate productivity of construction firms (Liao 2010). Second, market disorder and unhealthy competition in the project bidding will occur due to excessive competition, such as low-price bidding, loan construction, and bid rigging, which turn in a low-profit rate for construction firms (Zeng *et al*. 2005, Liao 2010, X. Liu and Zhang 2021). Third, the costs of labor will increase resulting from higher wages driven by excessive competition among firms for skilled labor (Yang 2016). Moreover, excessive agglomeration also leads to an increase in the price of other resources (e.g. rents of equipment and land price, etc.) (Rizov 2012, J. Liu *et al*. 2017). Thus, the excessive competition resulting from the congestion effect will hinder the improvement of TFP in the construction industry, due to the disorder of the market and increasing production costs.

Besides, excessive agglomeration will overburden the city infrastructure, leading to the side effects such as traffic jams (Broersma and van Dijk 2008). It is recognized that excessive agglomeration will cause traffic jams which reduce accessibility and increase the commute times among different places (Higgins *et al*. 2019). For example, Broersma and Van Dijk (2008) found that the declining labor productivity growth of Dutch firms is caused by frequent traffic congestion. A similar conclusion has been drawn in Indian firms and more evidence was provided which was the favorable effect of the improvements in access to the market through linking the inter-regional infrastructure (Lall *et al*. 2004). Given that transportation is important to the implementation of construction projects as described above, the infrastructure burden caused by the congestion effect does harm to the enhancement of TFP in the construction industry.

The competing results of the agglomeration effect and congestion effect

As described above, the IA can bring up the agglomeration effect to improve TFP in the construction industry, but it can be associated with several diseconomies of congestion effect. The agglomeration life cycle model proposed by Potter and Watts (2011) denotes the evolution of industrial agglomeration over time in different stages of the industry life cycle, leading to the results from agglomeration economics to dispersion economics. Thus, according to the agglomeration life cycle model and the previous empirical studies (Potter and Watts 2011, C. Hu *et al*. 2015, J. Liu *et al*. 2017, H. Yuan *et al*. 2020b), this study proposed that the beneficial agglomeration effect occurs initially and dominates the early stage of the agglomeration life cycle in the construction industry, then the congestion effect appears and offsets the positive externalities from agglomeration effect gradually as the development of industrial agglomeration. Finally, the congestion effect outweighs the agglomeration effect and diminishes TFP in the construction industry.

Given that the competition between the agglomeration effect and congestion effect will lead to different net impacts on TFP at different stages of the development of industrial agglomeration (C. Hu *et al*. 2015, J. Liu *et al*. 2017, H. Yuan *et al*. 2020b), the current study divides the impact of IA on TFP of the construction industry into two stages, i.e. embryonic stage and recession stage, according to the net effect. The embryonic stage is dominated by the agglomeration effect, as such, the industrial agglomeration will have a positive net impact on the improvement of TFP; while the recession stage is dominated by the congestion effect, as such the industrial agglomeration will have a negative net impact on the improvement of TFP.

Combining the theoretical and empirical analysis together, the impact mechanism of IA on TFP in the construction industry and the development of hypotheses are shown in Figure 1. The relationships between IA and TFP are different at different stages (i.e. embryonic or recession stage). Accordingly, the following hypotheses are proposed:

Hypothesis 1 (H_1): The IA has a positive impact on TFP in the construction industry, which means that the impact of IA on TFP is in the embryonic stage.

However, with the development of IA, the congestion effect will outweigh the agglomeration effect, when the impact of IA on TFP enters the recession stage at which the negative relationship between IA and TFP occurs. Accordingly, the hypothesis is proposed:

Hypothesis 2a (H_{2a}): The IA has a negative impact on TFP in the construction industry, which means that the impact of IA on TFP is in the recession stage.

If the time span of the data is long enough, the presented relationship of IA and TFP may show an inverted "U" shape, which can display the evolution of impact of IA on TFP from the embryonic stage to the recession stage. Therefore, the other sub-hypothesis is developed:

Hypothesis 2b (H_{2b}): There is a non-linear inverted "U" shape relationship between IA and TFP in the construction industry, which means that the impact of IA on TFP is in the recession stage. Such that when the level of IA crosses the turning point, the negative congestion effect dominates the impact, leading to the decrease in TFP.

Methods and data

The hypotheses proposed above pay more attention to the trend of the relationship between IA and TFP, i.e. positive correlation, negative correlation, and the existence of a turning point. Specifically, positive correlation and negative correlation mean that there is a linear relationship between IA and TFP, but the

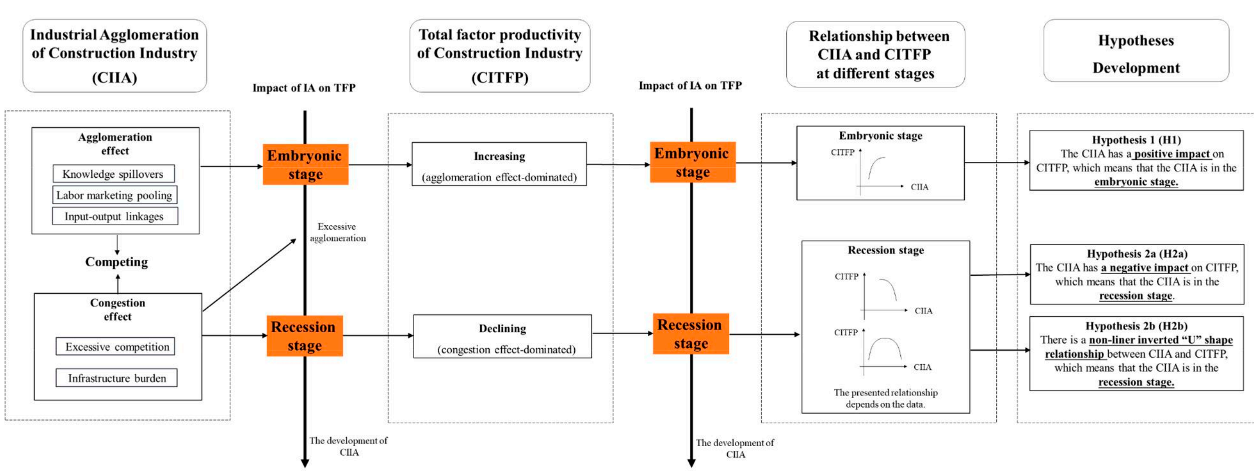

Figure 1. The impact mechanisms of IA on TFP and hypotheses development.

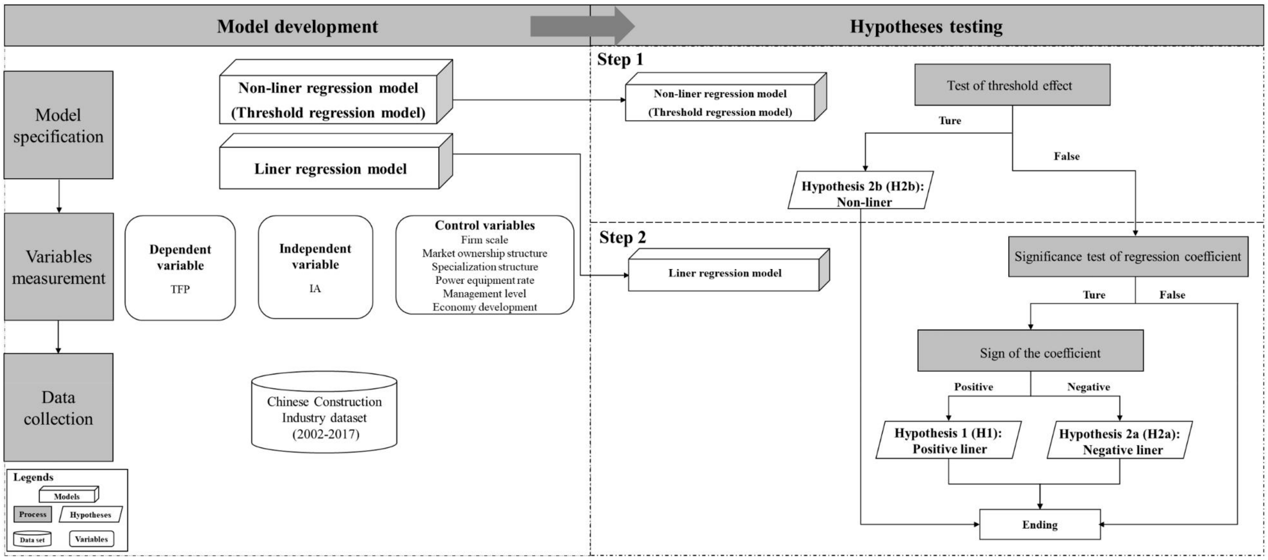

Figure 2. Diagram of research flow.

existence of a turning point refers to the non-linear relationship between IA and TFP. Thus, this study designs a two-step method to test the proposed hypotheses, with the non-linear regression model or linear regression model developed in each step. Since the relationship between IA and TFP is either linear (H_1 and H_{2a}) or non-linear (H_{2b}), the non-linear regression model is developed firstly to test H_{2b}. If the H_{2b} is valid, the H_1 and H_{2a} will not be tested. Otherwise, it will enter the next step to verify whether H_1 or H_{2a} is valid through the linear regression model. The research flow of this study is shown in Figure 2.

Regression model

Non-linear regression model

To test the non-linear relationship between IA and TFP, previous studies have applied the curvilinear analysis (Y. Zhang *et al*. 2021b) and threshold regression model (Zheng and Lin 2018). The former method needs to set the specific forms of function between the dependent variable and independent variable in advance and test the applicability of different functions (Y. Zhang *et al*. 2021b), but the latter does not need to set the function in advance to solve the nonlinearity among variables, which can establish different regression models within different threshold intervals via threshold test (Hansen 1999, Zheng and Lin 2018). The inverted U-shaped non-linear relationship hypothesized in H_{2b} will be supported once there is one or more than one turning points (corresponding to the threshold in the threshold regression model) discovered between IA and TFP, with no need to decide the specific function between IA and TFP in advance. Hence, the threshold regression model was selected to test the hypotheses because it could test the existence of turning points rather than the function.

The non-dynamic balanced panel threshold regression model proposed by Hansen (1999) not only fully considered the time series and richness of the sample, but also applied bootstrap method to test whether there is threshold effect. As such, following the empirical model adopted by Widodo *et al*. (2014) and Hansen (1999), the logarithmic forms of IA and TFP were selected as independent and dependent variables respectively. The non-linear threshold regression model was developed as follows:

$$\ln TFP_{it} = \beta_1 \ln IA_{it} \cdot 1(IA_{it} \leq \gamma) + \beta_2 \ln IA_{it} \cdot 1(IA_{it} > \gamma) + \beta_j \sum\nolimits_{j=3}^{n} \ln X_{j,it} + \vartheta_{it} + \varepsilon_{it}, \tag{1}$$

where subscripts i and t represent province and year respectively; $\beta_j (j = 1, 2, \ldots, n)$ represents the elasticity values of independent variables and control variables; γ refers to the threshold value; X represents a series of control variables; ϑ_{it} and ε_{it} represent the individual intercept term and the error term respectively. And $1(\cdot)$ is an indicative function and takes 1 or 0 depending on whether the expression in the bracket is valid.

The null hypotheses H_0: $\beta_1 = \beta_2$ was proposed to test whether there is a threshold effect, and Hansen (1999) established the likelihood ratio test (LR) statistics as follows.

$$LR = \frac{(SSR^* - SSR(\hat{\gamma}))}{SSR(\hat{\gamma})/N(T-1)}, \tag{2}$$

where SSR^{*} is the residual quadratic sum of the model when the threshold does not exist. $SSR(\hat{\gamma})$ is the residual quadratic sum of the model when there is a threshold. Also, Hansen (1999) proposed the bootstrap method to simulate progressive distribution of F-statistic and determine the threshold value of LR. If the null hypothesis is true, there is no threshold effect, otherwise there is threshold effect. Then, continuing to test the threshold and carrying out the regression model in each threshold interval.

Linear regression model

The linear regression model was used to test the linear relationship between IA and TFP. Similar to the establishment of the non-liner regression model, the logarithmic forms of IA and TFP were selected as independent and dependent variables respectively (Widodo *et al*. 2014, Hansen 1999). The linear regression model established in this paper was specified as:

$$\ln TFP_{it} = \beta_1 \ln IA_{it} + \beta_j \sum\nolimits_{j=2}^{n} \ln X_{j,it} + \varepsilon_{it}. \tag{3}$$

If there are unobservable fixed effects of province and time, the error term in the model is:

$$\varepsilon_{it} = \delta_i + \gamma_t + \mu_{it}, \tag{4}$$

where δ_i and γ_t represent fixed effects of province and time respectively, and μ_{it} refers to the random error.

Variables

Dependent variable: total factor productivity (TFP)

TFP level and TFP index are two commonly used indicator for TFP, with the former referring to the TFP value in one data point and the latter referring to the change of TFP value between two data points (O'Donnell 2012). The promotion of the TFP level rather than the TFP index is beneficial to the development of the construction industry in the early stage, especially in a situation of low productivity (Hasan *et al*. 2018). Thus, the TFP level was chosen as the dependent variable and was measured by the Färe-Primont DEA approach. TFP can be defined as the ratio of aggregate output to an aggregate input (O'Donnell 2012), which is shown in Eq. (5).

$$TFP_{it} = \frac{Q_{it}}{X_{it}}, \tag{5}$$

where $Q_{it} = Q(q_{it})$ denotes an aggregate output and $X_{it} = X(x_{it})$ denotes an aggregate input.

Then, it is necessary to select the indicators to measure the input and output. Regarding the input indicators, most of the studies select two input indicators (i.e. labor and capital), which are the representative elements during the production process (Chancellor and Lu 2016). Besides, the intermediate inputs, such as materials, energy, and services (Ruddock and Ruddock 2011), are also important input indicators. However, according to Y. Wang *et al*. (2021), when measuring input, more studies choose to ignore the intermediate inputs rather than taking them into consideration due to the data availability. Thus, based on previous studies, only labor and capital are chosen as the input indicators in this study, with the number of employees measuring the labor and the net value of fixed assets measuring the capital (W. Tan 2000).

In terms of output, total output value and total value added were the most selected output indicators (Ye *et al*. 2019, Y. Wang *et al*. 2020, 2021). The total output value of the construction industry is the sum of construction products produced by construction firms in monetary terms during an observed period, which includes the value generated by upstream industries and the added value in construction production activities (NBSC 2003–2021). The total value added of the construction industry refers to the net value of production and operation activities in monetary terms during an observed period, which excludes the value generated by upstream industries (Xue *et al*. 2008). Therefore, the total output value will enlarge the real output without considering intermediate inputs on the input side (Y. Wang *et al*. 2020). Corresponding to the input selections, the total value added was selected as the output indicator because it can avoid the double-counting of intermediate products from upstream industries (W. Tan 2000, Xue *et al*. 2008, Ye *et al*. 2019). Finally, we input the dataset into DPIN (version 3.0) to obtain the TFP level.

Independent variable: industrial agglomeration (IA)

According to the literature review, the location quotient was selected to denote the level of IA and the calculation of IA can be expressed as (Zhao *et al*. 2017, Kim *et al*. 2021):

$$IA_{it} = \frac{C_{it}/GDP_{it}}{\sum_{i=1}^{n} C_{it} / \sum_{i=1}^{n} GDP_{it}}, \tag{6}$$

where C_{it} is the total value added of the construction industry of i province in t year, and $\sum_{i=1}^{n} GDP_{it}$ means the sum of all industries' *GDP*.

Control variables

Various factors which have impacts on TFP have been identified from different aspects, such as market

Table 1. Descriptive statistics of variables.

Variable type	Variable name	Mean	Standard deviation	Minimum	Maximum
Dependent variable	Total factor productivity (TFP)	0.260	0.127	0.078	0.561
Independent variable	Industrial agglomeration (IA)	0.941	0.385	0.241	2.282
Control variables	Firm scale (FS)	12449	8555	1391	43710
	Market ownership structure (MOS)	0.099	0.064	0.012	0.505
	Specialization structure (SS)	2.161	1.708	0.286	14.545
	Power equipment rate (PER)	6.232	2.710	2.100	27.400
	Management level (ML)	0.039	0.013	0.014	0.086
	Economy development (ED)	33104	23998	3241	129042

structure, technical progress, construction management, economic development, etc. as mentioned in the Introduction Section. Although selecting more control variables tend to improve the fitting degree of the regression model, it will reduce the degree of freedom of the model. Therefore, considering the data availability and the results of previous research, six control variables, which have been regarded as the important impact factors on TFP in previous studies, were selected as follows:

Firm scale (*FS*), measured by the ratio of the total output value of the construction industry to the number of construction firms (B. Liu *et al*. 2015, Chen *et al*. 2017); *Market ownership structure* (*MOS*), measured by the ratio of the number of state-owned firms to the number of all firms (B. Liu *et al*. 2015, Chen *et al*. 2017). *Specialization Structure* (*SS*), which refers to the ratio of the number of general contractors to the number of specialty contractors (B. Liu *et al*. 2015, Chen *et al*. 2017); *Power equipment rate* (*PER*), measured by the ratio of the total power of owned machinery and equipment [1]to the number of all construction workers at the end of the year (D. Tan *et al*. 2015); *Management level* (*ML*), which is measured by the proportion of total management fees to the total output value of the construction industry (Arditi and Mochtar 2000); and *Economy development* (*ED*), i.e. per capita GDP (Chen *et al*. 2017).

Data source

The Chinese government has adopted a new statistical standard for the China Statistical Yearbook regarding the construction industry since 2002. The coverage of the new standard includes all the general contractors and subcontractors firms rather than all the construction firms with qualification criteria at or above Class 4[2] (NBSC 2003–2018). Besides, the data on the total value added of the Chinese construction industry at the provincial level have not been updated since 2018. In order to ensure the consistency and integrity of data, this study collected panel data of 31 provinces[3] in China (excluding Hong Kong, Macau, and Taiwan due to lack of data) from the "China Statistical Yearbook" and "China Statistical Yearbook on Construction" issued by National Bureau of Statistics of China from 2002 to 2017 (NBSC 2003–2018). Thus, the sample in this study includes the data of registered firms in each province, which were used to represent all the firms that carry out construction projects in that province, i.e. the population in this study (cf. Xue *et al*. 2008, Chancellor and Lu 2016, Chen *et al*. 2017). The variables and their statistical descriptions are summarized in Table 1 and the spatiotemporal changes of the dependent variable (TFP) and independent variable (IA) are shown in Figures 3 and 4.

As shown in Figures 3 and 4, the level of IA and TFP present several drastic changes during the observed period and deviations among different provinces, which is suitable for the analysis.

Results and discussions

The test of hypothesis H_{2b}: non-linear relationship

In order to test the non-linear relationship between IA and TFP as hypothesized in H_{2b}, a panel threshold regression model was developed assuming that there is no single threshold with IA as the threshold variable. If the threshold effect is proved in this model, hypothesis H_{2b} will be supported. LR statistic was developed for testing the threshold and Bootstrap times were set to 300. The results of the test are shown in Table 2.

According to Table 2, the null hypothesis that there is no single threshold is accepted. It revealed that there is no non-linear relationship between IA and TFP, thus H_{2b} is rejected. In other words, the development of IA in the construction industry in China did not meet a turning point during 2002–2017.

This finding shows a different phenomenon between the construction industry and the textile industry. Lin *et al*. (2011) found that an inverted U-shape non-linear relationship existed between IA and labor productivity in the Chinese textile industry based on the panel dataset from 2000 to 2005. The construction industry is characterized as a project-based

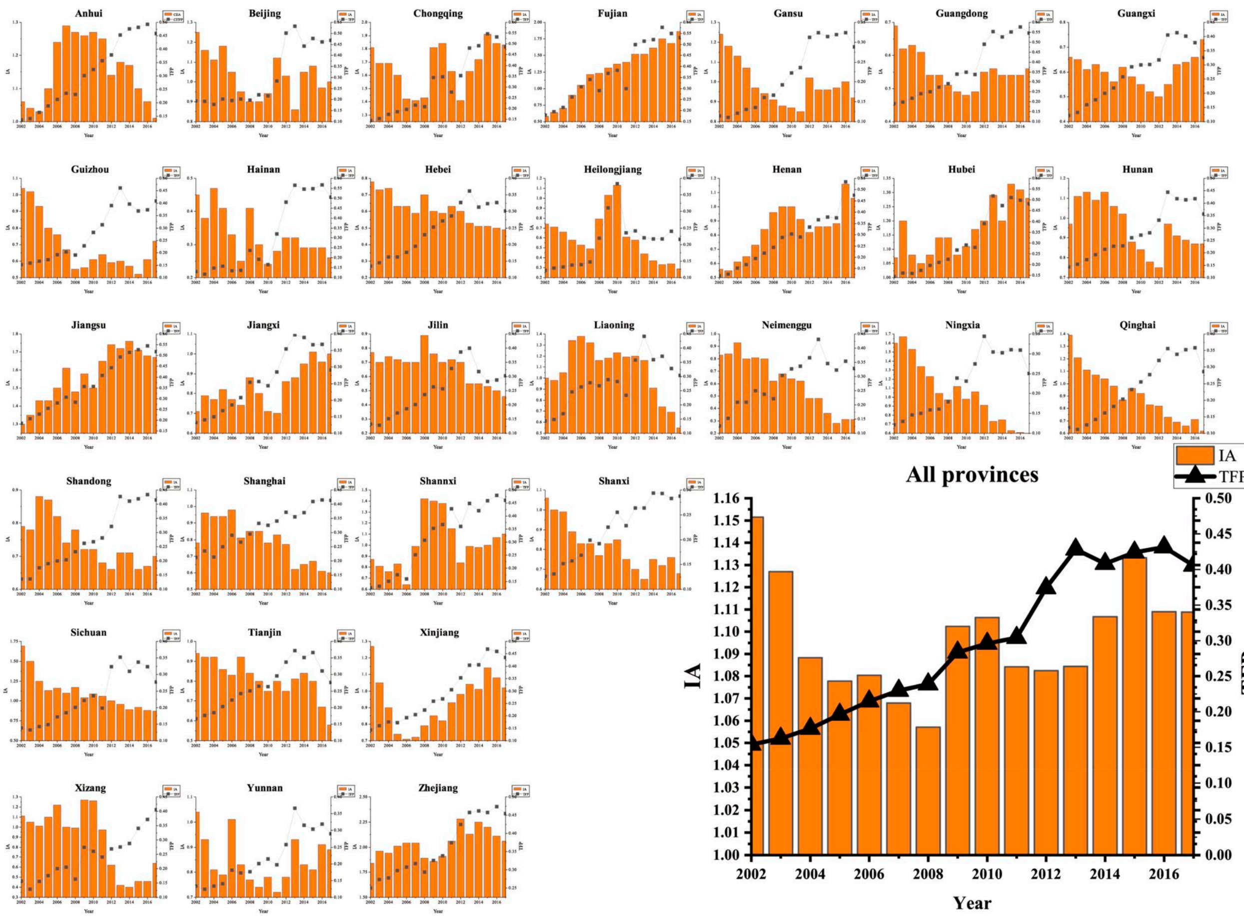

Figure 3. Temporal variation of IA and TFP.

industry, of which outputs are non-repeatable and one-off (J. Zhang *et al.* 2021a). This essence means that the formation of high-level IA may require a long time. However, the textile industry can be regarded as a raw material-oriented, market-oriented, and labor-oriented industry (Lin *et al.* 2011), therefore the formation of high-level IA may depend on relatively fixed production resources which makes the agglomeration formation easier than that of the construction industry. For example, the location quotient of the textile industry in Zhejiang reached 2 in 1997 and even reached 2.78 in 2013 based on the same calculation method of the current study (Wang 2018), but the location quotient of the construction industry in Zhejiang reached 2 in 2005 and fluctuated between 2 during 2005–2017 (see Figure 3). The discrepancy between the textile industry and construction industry may denote that they have different agglomeration life cycle, and the latter may take quite a long time to form the large agglomeration effect and cause the congestion effect. Therefore, the level of IA in the Chinese construction industry may be in an embryonic stage, which may not generate a congestion effect. A further test is required to support these opinions, and the linear regression model will be adopted to test H_1 and H_{2a} in the following section given that H_{2b} is rejected.

The test of hypotheses H_1 and H_{2a}: liner relationship

Based on the results of the pooled ordinary least square (POLS), Chow test, Lagrange Multiplier test, and Hausman test, this study chose the two-way fixed effects model (TWFE) as the panel linear regression model (Kartikasari and Merianti 2016). Therefore, this study applied the two-stage least squares (2SLS) regression method to solve the endogeneity problems based on TWFE (Wooldridge 2009). Besides, the generalized method of moments (GMM) regression method was applied to act as a coherence check with the results from the 2SLS regression method under the existence of autocorrelation and heteroskedasticity in the panel model, which will provide greater confidence in magnitude and sign of the estimated coefficients. The IPS (Im, Pesaran and Shin) unit root test

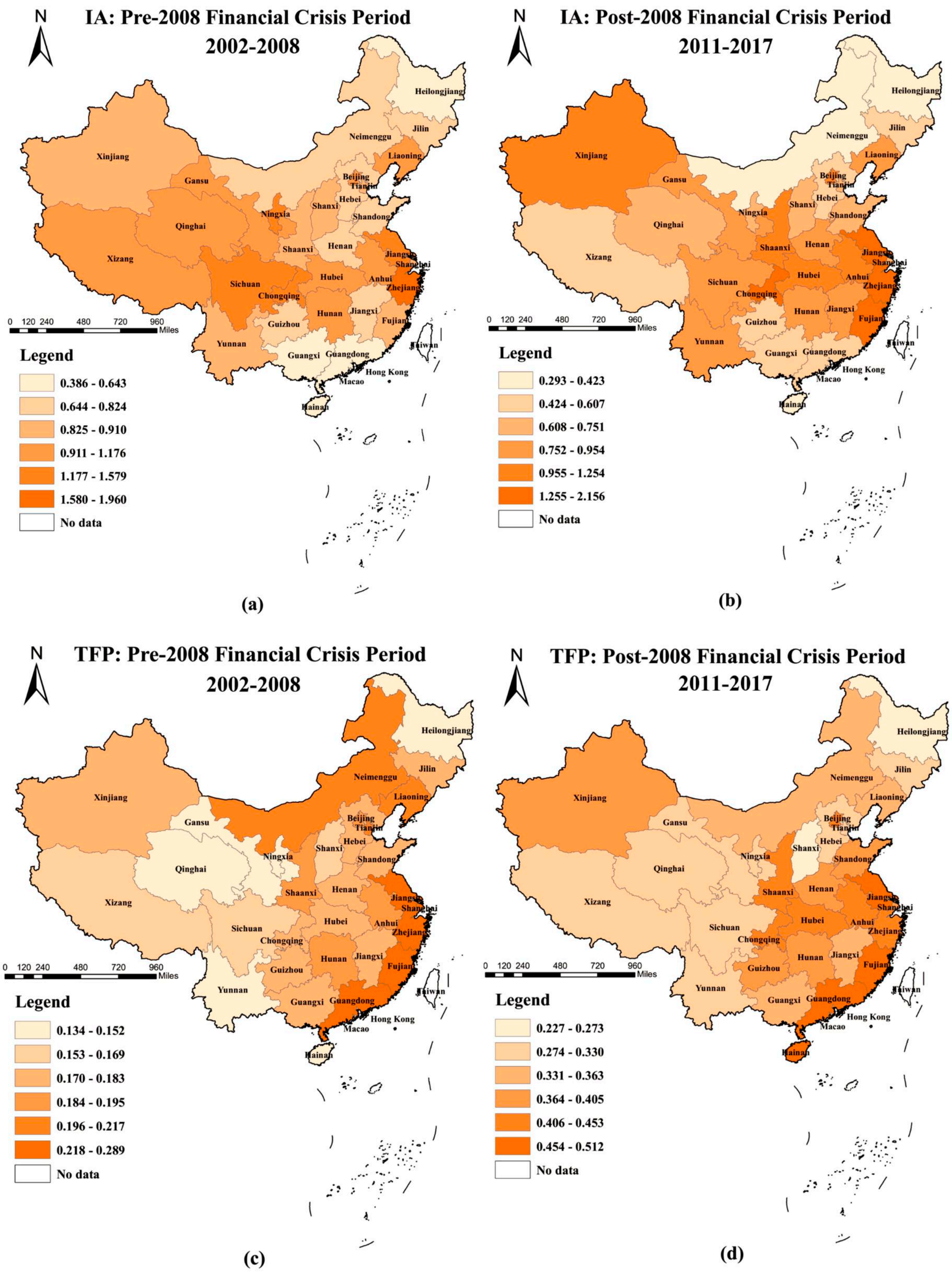

Figure 4. Spatial variation of IA and TFP.

and multiple collinearity test were conducted to exclude unit root and multicollinearity of variables (Im *et al.* 2003). Table 3 shows that all variables are stable and there is no obvious multicollinearity problem between variables.

The results of 2SLS and GMM are reported in Table 4 and the results of model selection tests are also listed for comparison. Without considering endogenous problems, the coefficient of IA in the model (4) is overestimated because the IA and ED are found as a pair of endogenetic variables in our test. Besides, the nearly consistent results of Model (5) and Model (6) also denote the robustness of the results of the 2SLS model under the coherence check of GMM. Therefore, looking back at Model (5), the positive coefficient of the IA basically passes the significance test at the 5% level, denoting that IA has a positive impact on TFP in the Chinese construction industry from 2002 to 2017. More specifically, the coefficient of IA is 0.179, which means that when the IA level increases by 1%, the TFP will increase 0.179%. Hence, the empirical results suggest that the H_1 is verified and thus H_{2a} is rejected.

The empirical results suggest that IA has a positive liner impact on TFP, which means that the impact of IA on TFP is in the embryonic stage and the agglomeration effect has been formed. Therefore, due to the existence of positive agglomeration externalities and the agglomeration life cycle of the construction industry, at least in the short term, the government should not concern too much about the occurrence of the congestion effect and should vigorously formulate preferential policies to encourage industrial agglomeration in the construction industry. For example, the people's government of Zhejiang province clearly put forward the goals of IA in one of the policy documents proposed in 2011: the agglomeration level of the construction industry needs to be further improved and the output value of the CR60 (i.e. the concentration ratio of top 60 firms) need to reach 40%, and the number of firms whose annual output value is more than 10 billion need to exceed 30 (PGZP 2011). As a result, Zhejiang has become the leading province of IA and TFP during the observed period.

Besides, IA has a positive impact on TFP via knowledge spillovers, labor marketing pooling, and input-output linkages according to the theoretical analysis. The illustrations and explanations of the agglomeration effect within the construction industry in China are described as follows. Taking Jiangsu and Zhejiang (the high-level IA areas) and Heilongjiang (the low-level IA area) as examples, the average number of labors working for the construction industry from 2002 to 2017 in Jiangsu and Zhejiang are 5.44 million and 5.10 million respectively, far higher than that of Heilongjiang (0.46 million) (NBSC 2003–2018). The above evidence supports the agglomeration effect of IA in Zhejiang and Jiangsu, which have formed a large labor pool. Moreover, the construction industry is linked to the upstream and downstream industries, including subcontractors, designers, surveyors, the supervisory consultation industry, etc. (Huo *et al.* 2020). Similarly, the average number of survey and design agencies from 2002 to 2017 in Jiangsu and Zhejiang are 1173 and 814 respectively, also higher than that in Heilongjiang (326) (NBSC 2003–2018). The development of the upstream and downstream industries is booming in Zhejiang and Jiangsu, which denotes that the input-output linkages in these provinces are closer, thus contributing to the higher TFP. Although the knowledge spillovers cannot be observed directly, it can lead to technological innovation (Z. Wang and N. Wang 2012, Bakar *et al.* 2016) which has been found to maintain the highest level in eastern areas of China (Chancellor and Lu 2016). Hence, the government and practitioners can promote the interaction of construction firms through face-to-face meetings, open-day events, shared training, etc. to strengthen the exchange of technology and management experience, thus maximizing the agglomeration advantages of the existing construction industry.

Of the control variables, in accordance with previous findings (B. Liu *et al.* 2015, Chen *et al.* 2017), the ES turns out to be a positive influencing factor of TFP. This finding suggests that large construction firms have advantages in resource relocation and

Table 2. Threshold effect test (bootstrap = 300).

Threshold	Fstat	Prob.	Crit10%	Crit5%	Crit1%
Single	15.64	0.16	17.65	22.90	34.05

Table 3. IPS unit root test and multicollinearity test.

	Unit root test				Multiple collinearity test
	No-trend of intercept		Trend of intercept		
Variables	Statistic	*p*-Value	Statistic	*p*-Value	VIF
lnTFP	−2.067	0.0194	−2.997	0.0014	–
lnIA	−0.004	0.4985	−2.717	0.0033	1.43
lnFS	−1.7412	0.0357	−2.1302	0.0216	5.81
lnMOS	−1.5822	0.0568	−1.1404	0.1271	2.82
lnSS	−2.9976	0.0014	−2.5455	0.0055	1.56
lnPER	−2.0648	0.0195	−1.6333	0.0512	1.36
lnML	−1.8549	0.0318	−2.9666	0.0015	2.77
lnED	−1.6955	0.0372	−2.7363	0.0029	6.67

Table 4. Regression results of IA on the TFP.

Methods	Dependent variable: lnTFP					
Variables	(1) POLS	(2) Fixed effects	(3) Radom effects	(4) TWFE	(5) 2SLS	(6) GMM
Cons	−8.279***	−8.798***	−8.503***	−5.820***	–	–
	(−29.99)	(−26.57)	(−28.76)	(−5.95)		
lnIA	0.056	0.174**	0.088	0.308***	0.179**	0.187***
	(0.99)	(2.70)	(1.33)	(3.30)	(2.48)	(2.62)
lnFS	0.282***	0.311***	0.337***	0.089	0.242***	0.243***
	(4.80)	(3.50)	(4.37)	(0.83)	(3.66)	(3.68)
lnMOS	−0.019	−0.120*	−0.115**	0.043	−0.057	−0.057
	(−0.32)	(−1.80)	(−2.36)	(0.40)	(−0.93)	(−0.93)
lnSS	0.136***	−0.123***	0.015	−0.096**	−0.196***	−0.203***
	(3.18)	(−2.91)	(0.34)	(−2.34)	(−4.18)	(−4.37)
lnML	−0.144	0.121	−0.005	0.060	0.099	0.095
	(−1.48)	(1.52)	(−0.06)	(0.72)	(1.64)	(1.57)
lnPER	0.029	0.031	0.045	−0.020	−0.035	−0.036
	(0.63)	(0.77)	(1.16)	(−0.47)	(−1.31)	(−1.36)
lnED	0.352***	0.454***	0.351***	0.345***	0.174***	0.168**
	(4.76)	(4.49)	(3.54)	(3.24)	(2.60)	(2.51)
Province fixed effects	–	Yes	Yes	Yes	Yes	Yes
Year fixed effects	–	–	–	Yes	Yes	Yes
Province clustering	Yes	Yes	Yes	Yes	Yes	Yes
Chow test	–	0.0000	–	–	–	–
LM test	–	–	0.0000	–	–	–
Hausman test	–	Sargan–Hansen statistic 126.868 (0.0000***)		–	–	–
Joint significance test	–	–	–	0.0000***	–	–
Adj. R^2	0.86	0.94	0.94	0.95	0.93	0.93
Observation	496	496	496	496	434	434

Tests for 2SLS and GMM

Test	Statistic	
Under identification test	KP-LM statistic = 71.271	p-Value = 0.000 < 0.05
Weak identification test	KP-F statistic = 51.601 > 8.18 (15% maximal IV size)	
Overidentification test	Hansen J statistic = 1.979	p-Value = 0.1595 > 0.1
Endogeneity test	Chi-sq(2) = 24.374	p-Value = 0.000 < 0.05

Notes: 1. Beneath each coefficient estimate is the t-statistic based on robust standard errors adjusted for clustering by province which is robust under heteroscedasticity and autocorrelation. 2. Chow test is a test with the null hypothesis that all δ_i=0. 3. LM test is for individual heterogeneity with the null hypothesis that σ_δ^2=0. 4. Hausman test under clustering standard errors has the null hypothesis of irrelevance between individual heterogeneity (δ_i) and explanatory variables. 5. The null hypothesis of the joint significance test of annual dummy variables is no time-fixed effect. 6. Under identification test's null hypothesis is that the equation is under identified. 7. If KP-F statistic of weak identification test is bigger than Stock–Yogo weak ID test critical values of 15% maximal IV size, then excluded instruments are correlated with the endogenous regressors. 8. The null hypothesis of overidentification test is that the excluded instruments are exogenous (i.e. uncorrelated with error terms). 9. The null hypothesis of endogeneity test is that the specified endogenous regressors are exogenous. 10. ***, **, * each denotes statistical significance at the 1% level, 5% level and 10% level, respectively.

innovation. Besides, there is also a positive relationship between ED and TFP, which is in line with the finding of Chen *et al*. (2017). Under the support of the local government, a developed area tends to provide more chances for the construction firms to enhance their innovation capability and management skills due to the huge demand for construction products, which can be illustrated by the construction of the Hong Kong-Zhuhai-Macao Bridge in Guangdong province (Zhu *et al*. 2018). However, a negative relationship is found between SS and TFP, which is also consistent with the finding of Chen *et al*. (2017). It implies that the productivity of general contractors is lower than that of subcontractors, thus the specialization of the contractors should be emphasized. Thus, some support and training should be carried out to encourage the general contractors to expand their firm scale and the subcontractors to promote their skills, which requires an effective general contract and subcontract system.

Conclusions and policy implications

This study has investigated the impact mechanism of IA on TFP at different stages of the agglomeration life cycle in the construction industry theoretically and conducted an empirical analysis to clarify the relationship between IA and TFP based on the provincial panel data from 2002 to 2017 in China. It was proposed that industrial agglomeration results in both the agglomeration effect and congestion effect in the construction industry, thus the net industrial agglomeration effect depends on the competition between these two opposite effects. Based on the theoretical analysis, IA and TFP were measured based on location quotient and the Färe-Primont DEA approach respectively and acted as the independent variable and dependent variable in the established non-linear model and liner regression model. The empirical results present a linear positive relationship between IA and TFP and the impact of IA on TFP in the

Chinese construction industry is in the embryonic stage of the agglomeration life cycle. Besides, the firm scale and economic development level are beneficial to the improvement of TFP, whereas the effect of specialization structure is negative.

The findings of this study have contributed to the existing knowledge in three aspects. Firstly, unlike previous studies which ignored the impact of IA on TFP, this study has extended the TFP research from the manufacturing industry, textile industry, tourism, etc. to the construction industry through the investigation of the impact of IA. Secondly, this study further developed the hypotheses of the relationship between IA and TFP based on the competing results of the agglomeration effect and congestion effect of IA, which further clarified the relationship between IA and TFP. Moreover, this study applied the threshold model to test the non-linear relationship between IA and TFP, which has extended the application of this model to the construction industry.

Our findings also provide some important policy implications to make the best use of IA as the engine of the improvement of TFP in the embryonic stage of IA in the Chinese construction industry. Firstly, the government should encourage the agglomeration of construction firms to improve the TFP, such as the introduction of the industrial park, tax incentives for the start-ups, and encouragement of cooperation of the top firms and new firms. Secondly, the government and practitioners can promote the interaction of construction firms to maximize the agglomeration effect of the existing construction industry. Besides, some support and training should be carried out to encourage the general contractors to expand their firm scale and the subcontractors to promote their skills.

Since agglomeration diseconomies may occur as the level of IA increases to a certain degree, the government should note this possibility, especially in the eastern coastal area. Thus, firstly, the provincial government needs to monitor the agglomeration status of each province, especially the eastern coastal area. Once the agglomeration diseconomies appear, it is a signal for the central government that the impact of IA on TFP of the Chinese construction industry will gradually enter the recession stage. The provincial government and central government need to make a prevention plan to lower the industrial agglomeration level or lower the congestion effect brought by the industrial agglomeration. For example, to disperse the construction firms to other provinces to lower the industrial agglomeration or to improve the traffic infrastructure to lower the congestion effect.

Although some new insights have been provided, this study is limited in the following aspects. Firstly, regarding the input indicator for TFP, this study takes labor and capital into consideration and ignores such inputs as materials and energy due to data availability. Although such conduct was adopted and deemed acceptable by many relevant studies (Chancellor and Lu 2016, Y. Wang *et al*. 2020), future study is recommended to include these indicators to calculate the input of TFP and use total output value to calculate the output when the data is available. And the measurement of TFP in China can only cover 2002–2017 due to the data availability, but the following research will be conducted to test whether the development of IA has met the turning point once the relevant data is available. Secondly, the total value added is used to calculate the dependent variable and is also used to calculate the independent variable and two control variables in the regression model. Although by using DEA, the dependent variable is measured by a distance between a decision-making unit and the envelope formed by all decision-making units based on the evaluation model, thus helps avoid the problem of fake correlation to some extent, future study is recommended to change the relevant variables to avoid the possible problem. Thirdly, based on Figure 3, we could infer that different provinces and even different countries may be in different stages of the development of IA, thus some systematic comparisons between the eastern, central, and western regions in China suggested by Luo *et al*. (2019) will be conducted and further exploration on the antecedents of IA is needed to explain the difference of IA in different regions. Fourthly, the policy is an important influence factor on TFP. Although we treated the impact of policy on TFP as indirect, assuming that the policy influences the TFP by influencing other factors, such as management level, market structure, economic development, etc., and tried to eliminate the impact of policy by controlling these factors in the study, the relationship between policies and control variables mentioned above may have an impact on TFP. Moreover, the other control variables viewed from the demand side, such as the consumer price index and the number of contracts, can be added to the regression model. Thus, future studies can explore the relationships between the policy, more control variables, and TFP.

Notes

1. Power refers to the amount of work done (W) by the object in unit time (T), that is, power is a physical quantity describing the speed of work done, calculated with the equation $P = W/T$. Total power of machinery and equipment refers to the sum of the rated power that the firm's owned construction machinery, production equipment, transportation equipment, and other equipment (as the registered fixed assets) have produced. This data is collected and counted by the National Bureau of Statistics of China (NBSC).
2. The Chinese government evaluated the construction firms' qualifications based on their labor level, management level, financial level, equipment level, construction capabilities, and performance, and then classified the qualified firms into four classes. Class 1 is the top class, and Class 4 is the lowest class. Before 2002, the China Statistical Yearbook only collected data of the construction firms with qualification criteria at or above Class 4, meaning that only the data of the qualified firms are collected and analyzed. After 2002, the data collected covers all the general contractors and subcontractors firms, including both the qualified firms and the unqualified ones.
3. There are 34 provinces in China, including 31 provinces in Mainland China, and three special administration regions, including Hongkong, Macao, and Taiwan. Hongkong, Macao, and Taiwan have different statistical systems compared with Mainland China. Thus, the "China Statistical Yearbook" and "China Statistical Yearbook on Construction" do not cover Hongkong, Macao, and Taiwan, which makes the data about these three provinces poor.

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